Neural Disparity Map Estimation from Stereo Image

Nadia Baha and Slimane Larabi
Computer Science Department, University of Science and Technology Houari Boumediene, Algeria

Abstract: *In this paper, we propose a new approach of dense disparity map computing based on the neural network from pair of stereo images. Our approach divides the disparity map computing into two main steps. The first one deals with computing the initial disparity map using a neuronal method Back-Propagation (BP). The BP network, using differential features as input training data can learn the functional relationship between differential features and the matching degree. Whereas, the second one presents a very simple and fast method to refine the initial disparity map by using image segmentation so an accurate result can be acquired. Experimental results on real data sets were conducted for evaluating the neural model proposed.*

Keywords: *Neural network, disparity map, segmentation, uncalibrated cameras.*

Received September 29, 2009; accepted August 10, 2010

1. Introduction

Stereo vision is a process which transforms the information of two planes images into a 3D description of the scene and recovers depth information in terms of the exact distance. With depth information, one can create models of the terrain and other natural environments for use in various applications, such as virtual reality, flight simulation and robotics. Due to its inherent characteristics, stereo vision is a better choice to reconstruct 3D coordinate of captured scenes. Active techniques utilize ultrasonic transducers or laser to illuminate the work space, so that they yield fast and accurate depth information [8, 16]. However, there are limitations to these techniques with respect to the measurement range and the hardware cost.

Passive technique based on computer vision is less sensitive to environments and typically requires a simpler and less expensive setup for range sensing. Those approaches are able to estimate depth information from acquired images and camera parameters [6, 7, 17, 23].

One of the most difficult problems in the depth estimation using passive techniques is to find the corresponding point (P_L, P_R). Indeed, assume that a point P in the scene is projected onto two cameras image planes P_L and P_R respectively. When the imaging geometry is known, the disparity between these two locations provides an estimate of the corresponding 3D position. Specifically, the location of P can be calculated from the known information, P_L and P_R and the internal and external parameters of these two cameras, such as the focal lengths and the positions of the two cameras.

The parallel configuration shown in Figure 1, where one point P(X,Y,Z) is projected onto the left and right imaging planes at $P_L(X_L,Y_L)$ and $P_R(X_R,Y_R)$, respectively. The difference (X_L-X_R) is the disparity. The disparity is inversely proportional to depth. A disparity map that records the disparity for each image point is therefore sufficient for a complete 3D reconstruction of the scene.

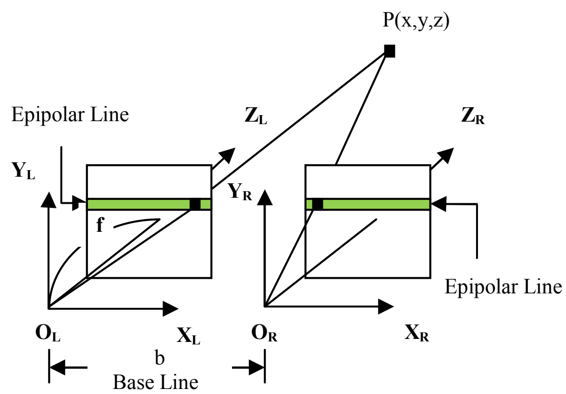


Figure 1. The parallel configuration in stereo vision.

A great number of approaches for disparity map estimation have been proposed in the literature, including features-based, area-based, DSI-based [5, 4] and energy-based approaches. A survey for the different approaches can be found in [27]. Area-based techniques [18, 19] utilize the correlation between the intensity patterns in the neighbourhood of a pixel in the left image and those in the neighbourhood of a corresponding pixel at the right image. They are simple and fast. The Sum of the Squared Difference (SSD) or auto-correlation has often been used as a criterion to determine the best matching pair. However, the size of the window can significantly affect the matching accuracy. Kanade and Okutomi [18] have presented an adaptive window algorithm with impressive results. Yet, it is virtually impossible to correctly match pixels using only information about distortion and variation inside a window area. Feature-based techniques [10, 12, 24, 25], instead, use symbolic features derived from intensity images rather than image intensities. Symbolic features, such as edge points and edge segments, are often used in these techniques. Since feature-based techniques allow simple comparisons between the attributes of features, they are generally faster and more accurate than area-based methods. However, it is a problem to find an appropriate interpolation method for non-featured areas, especially in case where reconstruction of a 3D surface is desired.

The energy-based approaches [1, 22] are time consuming. They are very accurate though. While these techniques achieve satisfactory results in certain situations, they are often implemented using numerical schemes which may be computationally intensive.

Also, a neural network has already been used to compute the degree of matching between two pixels located on two different images in stereo vision [26]. The structure of the proposed system [26] is composed of 5 layers and the input weights of neurons are pre-adjusted and no training of the network has been done.

In this paper, we propose a new approach for computing a dense disparity map based on the Artificial Neural Networks (ANN) from uncalibrated cameras. The goal is to combine the advantages of the area-based and feature-based methods. Our approach divides the matching process into two steps: initial matching and refinement of disparity map. Initial disparity map is first approximated by neuronal method so called Back-Propagation (BP) neural network. Then a segmented method is applied to the left and the right images where pixels are matched on a segment by segment basis. This step will allow us to refine the initial disparity so an accurate result can be acquired.

This paper is organised as follows: section 2 presents the stages of the proposed method. In section 3, experiments on real image and an analysis of the results are presented. Finally, section 4 concludes the paper with some remarks.

2. Proposed Approach

In this section, we describe the basic steps of our approach. We show how theses steps can be performed robustly.

Figure 2 shows the general view of our method of disparity map computation.

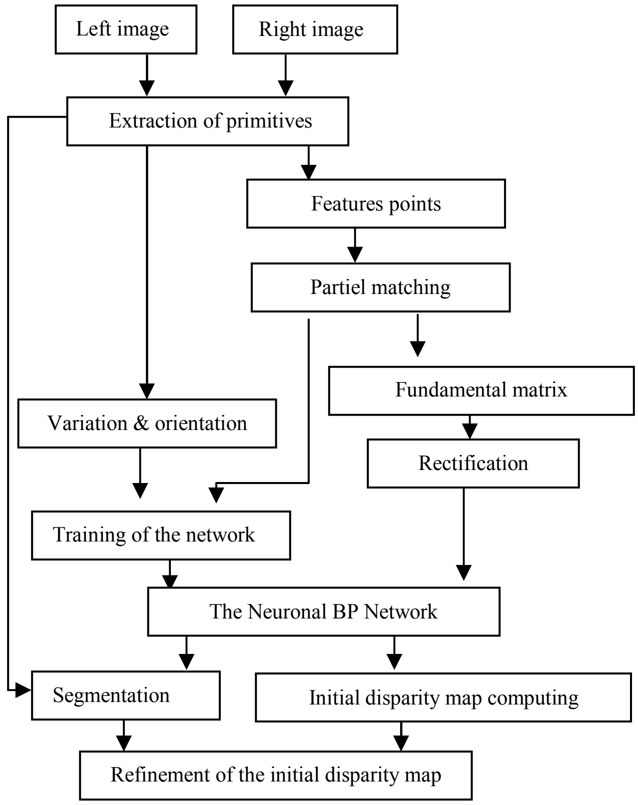


Figure 2. Block diagram of the overall process.

2.1. System Overview

The stereo images have been acquired from two CCD cameras mounted on mobile robot. It should be noted that in this work the cameras are arbitrarily configured. Thus, we can generate a parallel configuration through the process of rectification. In the next section, we describe the different steps of the rectification process.

2.1.1. Detection of the Features Points and Matching

The proposed method starts by extracting a set of feature points from each of the two images by using the detector of Harris [12]. These points are then matched using the normalized correlation named ZNCC [30]. In order to validate the correspondence between the points, the matching is done from the left image to the right image and from the right image to the left image. A valid match is considered only for those points that yield the best correlation score [2]. In addition, these points will be used in the training of the BP network. Figure 3 shows the left and right images with features points.

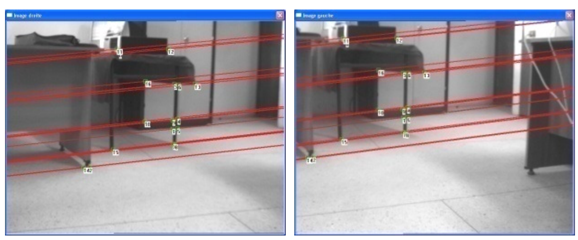


Figure 3. Left and right images overlaid with features points.

2.1.2. Estimation of the Fundamental Matrix

The fundamental matrix F links the left image to the right image. This means that for each point of the image plane of the left camera, the fundamental matrix 'F' gives us the epipolar line corresponding to it in the image plane of the right camera.

$$P_R^T F P_L = 0 \tag{1}$$

Where P(X,Y,Z) is the 3D point and $P_R(X_R,Y_R)$, its projection in the right image and $P_L(X_L,Y_L)$ its projection in the left image. To estimate the parameters of the fundamental matrix, several methods have been presented in the literature [3, 21, 28]. Most of these methods use a given number of pairs of matched points in the pair images: we can find the linear methods and the non linear methods. In our case, we use the non linear methods. Although they are difficult to implement, they offer many advantages: first they are robust, second they minimize the errors of matching, and third they achieve a better estimation of the fundamental matrix [21]. Therefore, we use the methods of Gauss-Newton and Levenberg-Marquardts [20].

2.1.3. Rectification of the Stereo Image

A constraint that is often considered in stereo vision systems is the epipolar geometry. This constraint states that any point lying on an epipolar line in one image necessarily corresponds to a point lying on the homologous epipolar line in the other image. Thus, the rectification is an important step since it allows the use of a simple epipolar geometry in which the epipolar lines are parallel to the lines of images [13, 29]. After rectification of the two images, the matched points have necessarily the same ordinate in the two images. Therefore, the search of the point of the second image corresponding to a given point of the first image is only limited to a one-dimensional search along a horizontal line of the second image is situated to the same ordinate, rather than a bi-dimensional research in a region of the second image. We have chosen to implement the described method in [29] it is based only on the knowledge of the fundamental matrix and the epipolar constraint to rectify a pair of images. It consists in determining two matrixes of rectification one for the left image and the other for the right image. Figure 4 shows an example of the left and right image obtained after rectification step.

Figure 4. Left and right images obtained after the rectification step.

2.2. Dense Disparity Map Estimation from Stereo Images

The disparity map calculation is expensive both in cost and in time. To overcome the two costs, we propose in this paper the use of an ANN.

An ANN is a network of neurons. The network has an input and an output. It can be trained to provide the right output for a certain input. A neuron is responsible for simple operations, but the whole network can make parallel calculations as the result of its wide parallel structure. The neurons have some inputs with input weights. The inputs are summed up and fed into a so called transfer function. The output of the transfer function is considered as the output of the neuron. This output can be further connected into the inputs of other neurons resulting in a vast network of neurons [14, 15, 24]. A neural network derives its computing power through, first, its massive parallel distributed structure and, second, its ability to learn and, Therefore, to generalize. The generalization refers to the production by the network of reasonable outputs for inputs not encountered during training. The structure of a neuron is shown on Figure 5.

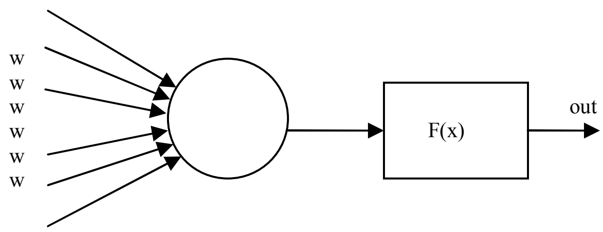


Figure 5. A neuron.

2.2.1. Initial Disparity Map

2.2.1.1. The Differential Input Features

Because the intensity value of each pixel is sensitive to the change in contrast and illumination, and despite the fact that intensity is the most common information used in matching process, the variation and orientation of each pixel deserve more detailed investigation with regard to their use as features. In this presented system, three pixel properties will be used in the comparison. If the intensity of an arbitrary pixel in location (x,y) is given by $f(x,y)$, the gradient of $f(x,y)$ is defined as:

$$\nabla f = [G_x, G_y] = [(\partial f / \partial_x), (\partial f / \partial_y)] \tag{2}$$

And its magnitude is defined as the variation of $f(x,y)$ and is written as:

$$|\nabla f| = mag(\nabla f) = [G_x^2 + G_y^2]^{1/2} \tag{3}$$

The orientation $\alpha(x,y)$ of the vector ∇f at (x,y) is:

$$\alpha(x,y) = \tan^{-1}(G_x / G_y) \tag{4}$$

In this work, the variation and the orientation values are all normalized to [0,255]. The Sobel operator gives good approximations of Gx and Gy [9]. Using the Sobel operator in feature extraction has two advantages: It can simultaneously and quickly calculate the variation and the orientation, and yields accurate orientations. Each pixel in the left and the right image has three basic features: Intensity, variation and orientation. When the BP network is used to compute the matching degree between two pixels from the left and right images, each input vector in fact consists of data from two 7×7 windows (one from the left image, the other from the right) in which the centres are the pixels to be matched. In particular, the differences between the three features are calculated for each 7×7 window to form a 147-Dimensional input feature vector. That is:

$$\begin{aligned} &\textit{Differences of Indensity}=f_{Li}-f_{Ri},\\ &\textit{Differences of Variation}=|\nabla f_{Li}|-|\nabla f_{Ri}|,\\ &\textit{Differences of Orientation}=\alpha_{Li}-\alpha_{Ri}, \end{aligned} \tag{5}$$

Where f_{Li}, $|\nabla f_{Li}|$, α_{Li} and f_{Ri}, $|\nabla f_{Ri}|$, α_{Ri} are the intensity, the variation and the orientation values of the i^{th} pixel in the left and the right images, respectively. Note that these differential features constitute the actual input vectors both in the training and in matching processes. Algorithm 1 in Figure 6 shows how this differential feature vector is generated.

Algorithm 1
Input: Left image, right image
Begin For each image do
- Apply the Sobel operator to each image.
- Difference of intensity= $f_{Li}-f_{Ri}$,
- Difference of Variation = $|\nabla f_{Li}|-|\nabla f_{Ri}|$,
- Difference of orientation = $\alpha_{Li}-\alpha_{Ri}$,
End,
End.
Output: Vectors of differential features.

Figure 6. Algorithm of differential features extraction.

2.2.1.2. The BP Network

- *Learning Procedure*: The neural correlation network must be trained with the learning procedure before computing the matching degree for each pixel. To prepare the training data, hundred pairs of matched and unmatched pixels are randomly selected to offline train the BP network. During training, the differences in intensity, variation and orientation between two local windows are fed to the BP network. After the training, the BP network should have the ability to differentiate the matched pairs from unmatched ones. The trained BP network is first used to generate an initial or primitive disparity map, which will then be used as a reference map for the subsequent matching process. This paper presents the use of the approximation capability function of the BP network to replace the traditional auto-correlation or SSD. Kolmogorov's theorem [15], which essentially states that the BP network can implement any function of practical interest to any desired degree of accuracy.

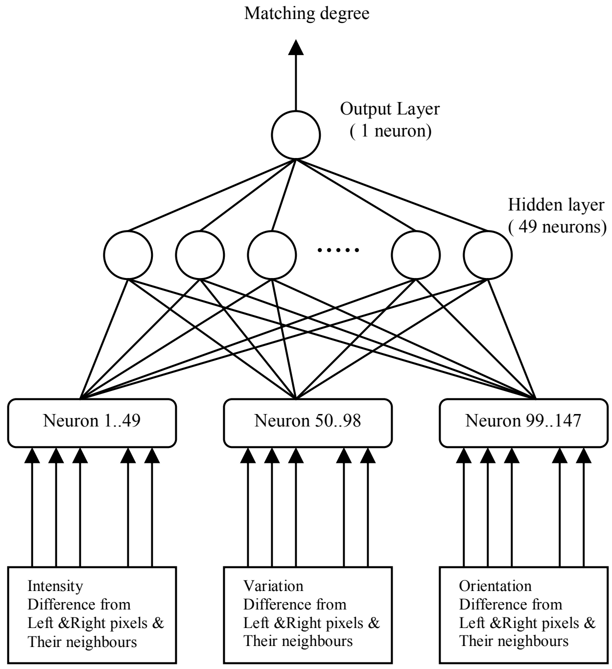


Figure 7. The BP neural network.

Thus, unlike traditional area-based methods, the BP network can learn to approximate any functional mapping between well-defined input output vectors. Figure 7 shows the architecture of the three-layer BP network that we used in this paper. The input layer has 147 neurons (=7×7×3, i.e., two 7×7 windows from the left and right images). The hidden layer contains 49 perceptron-type neurons: The matching-degree is then computed for a given disparity d as the sum of three attributes (intensity, gradient magnitude and orientation). A perceptron output neuron gives a real number: Matching-degree, such as: 0.0≤matching degree≤1.0. A few feature vectors of matched and unmatched pixel-pairs are sampled as training data. During the training, whenever a match pair appears in the input, the network is taught to output a target value of 1.0 by propagating the *Error=1.0− matching degree* back to the hidden layer; Otherwise, *Error=matching degree-0.0*, when a mismatch occurs. It means that we teach the network to give the matching degree value close to 1 for good match pair and the value close to 0 for a bad match pair.

- *Initial Disparity Map Computing*: Initially, a primitive disparity map is generated by the BP network itself. Then, the map is refined by a matching process which is based on the image segmentation.

As in the training process, we use differential features to generate the primitive disparity map. We first note that, under the geometric constraint, the larger the image size is, the greater the value of maximum disparity can be. For example, for a 128×128 image, the corresponding maximum disparity (denoted as dispMax) normally will not exceed 10, whereas for a 256×256 image, the corresponding dispMax normally is less than 20. Starting from the upper left pixel in the left image, the best matching pixel in the right image is determined pixel by pixel. Specifically, for an arbitrary matching pixel in the left image $P_L(X_L,Y_L)$, we compute the matching degrees for the next dispMax pixels located to the left of the $P_R(X_R,Y_R)$ in the right image, where $Y_R=Y_L$. Among the candidates $P_R(X_R,Y_R)$, $P_R(X_R-1,Y_R)$, $P_R(X_R-2,Y_R)$,.... $P_R(X_R-\text{dispMax},Y_R)$, the one that produces the largest output matching-degree is chosen. The process continues so forth until all the pixels are matched and the corresponding disparities are obtained, the primitive disparity map is drawn by assigning to the point that has the largest disparity the highest intensity level (255), and to the one with null disparity an intensity level of zero. The Figures 8 and 9 shows the Algorithms 2 and 3 that describes the initial disparity map computing.

Algorithm 2
Input: dispMax: Maximal disparity in the images pair, left image, right image.
Begin / Initial disparity map computing*/*
For each pixel $P_L(n,m)$ in left image
Do
For each pixel $P_R(x,m)$ in the right image and x belongs to [n, n- dispMax]
Do
- Calculate the matching degree between P_L and P_R (see algorithm 3),
- Select the pair of pixel having the maximum matching degree,
- Disparity (P_L, P_R)= n – x,
- Intensity (n, m) = Disparity (P_L,P_R) normalized between [0, 255].
End,
End,
End.
Output: Initial disparity map.

Figure 8. Initial disparity map algorithm.

Algorithm 3
Input: The neuronal network with 3 layers (147, 49, 1),
P_L (n, m): pixel in the left image,
P_R (n', m'): pixel in the right image,
α: a constant Initialized to 1.
Begin / Calculation of the matching degree between 2 pixels by a neuronal network */*
For i belongs to [-3, +3]
Do For j belongs to [-3, +3]
Do
- Input (neurone α) = intensity (n+i, m+j) - intensity (n'+i, m'+j),
- Input (neurone α+49) = variation (n+i, m+j) - variation (n'+I, m'+j),
-Input (neurone α+98) = orientation (n+i, m+j) - orientation (n'+i, m'+j),
-Matching -degree= output (neurone of the output),
- α = α + 1.
End,
End,
End.
Output: Matching -degree.

Figure 9. Algorithm of calculation of the matching degree between 2 pixels.

2.3. Disparity Map Refinement

After the initial disparity map is obtained by applying the BP network, a method of image segmentation is used to refine this map in order to achieve more accurate disparity.

2.3.1. Segmentation of Images

The segmentation step consists to extract the regions constituted by pixels of very close luminous intensity. In our case, we use the pyramidal segmentation method [31] witch consists to segment the image recursively.

2.3.2. Final Disparity Map

In this section, we present our method to refine the initial disparity map. After training, the BP network is first used to generate an initial disparity map. With the segmentation results and the initial map, a matching algorithm that incorporates the BP network is then applied to refine the map in a segment by segment manner. The matching process continues until all segments are matched. An image can be viewed as a set of several segments (areas), and we note that a pixel in the left image might have several pixels with high matching-degrees in the right image.

In order to effectively reduce the number of unmatched pixels and reduce the distortion caused by an unnecessary interpolation during surface reconstruction, our idea consists to classify the pixels in both input images into several segments using a segmentation image method. Pixels that belong to the same segment in the feature space should have similar characteristics. Therefore, pixels in the *j*th segment in left image tend to have matching pixels in the same segment in the right image. Performing segmentation before matching should greatly reduce the search space needed to find the corresponding pixels and increase the likelihood of correct matches.

Step 1 of Algorithm 4 describes how to search similar segments. We can say that two segments are similar if they have roughly the same intensity, the same number of pixels and the same ordinate. Then, for each segment S_L of the left image, search the segment S_R of the right image corresponding to S_L. Then, the pair (S_L, S_R) is searched and saved. We believe that two pixels belonging to the same segment have a good chance to become a matching pair.

The BP network computes the matching-degrees between an arbitrary pixel in the i^{th} segment in the left image and pixels in the same segment in the right image. We denote those pixels that have an output matching-degree>0.9 as the candidate set *C*. Then, the best match (in the right image) for the said pixel will be determined by applying various constraints on each pixel in *C* so as to exclude the incorrect one. These constraints are the epipolar and geometric constraints like: epipolar line constraint, ordering constraint and continuity constraint. We also note that the best match is chosen as the one that has the maximum value of matching degree. The algorithm of the disparity map refinement is illustrated by the Figure 10.

Algorithm 4
Input: initial disparity map,
{S_L}, {S_R}: Set of segments in the left and right images,
Step 1:
Begin / Find the corresponding segments*/*
For each segment S_L of the left image
Do
For each segment S_R of the right image
Do
If ([(S_L, S_R) have the same ordinate + Δy] and
[(S_L, S_R) have the same intensity + ΔI] and
[(S_L, S_R) have the same number of pixels + Δn])
Then save the corresponding (S_L, S_R)
End,
End, End,
End,
Step 2:
Begin
/ Refinement of the initial disparity map */*
For each segment S_L of the left image
Do
For each segment S_R of the right image corresponding to S_L
Do
For each pixel of S_L Do
- Find candidate pixels in S_R whose matching- degree >0.9 (using the BP network),
- Apply the geometric and epipolar constraints,
- If there are candidates then update the disparity value.
End,
End,
End.
Output: Final disparity map

Figure 10. Disparity map refinement algorithm.

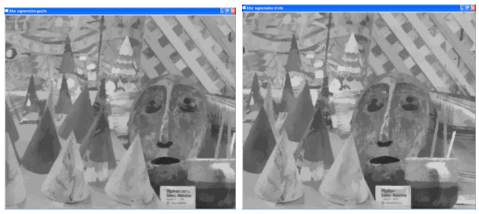
3. Experimental Results

In the following, we will show how the proposed neural method can be applied to achieve accurate disparity map. After training, the BP network is first used to generate an initial disparity map. With the segmentation results and the initial map, a matching algorithm that incorporates the BP network is then applied to refine the map in a segment-by segment basis. The BP network, we used had 7x7x3 input neurons, 49 neurons in the hidden layer and 1 output neuron.

In this section, we report the results of our approach using the standard data sets available at the Middlebury Website [32]. As suggested on this site, we have tested our method on four images (Cones, Teddy, Venus, Tsukuba,). Figure 11 shows the result of the segmentation method on the cone image. Figure 12 illustrates the results of computing a dense disparity map: from left to right: real images, initial disparity maps, and final disparity maps.

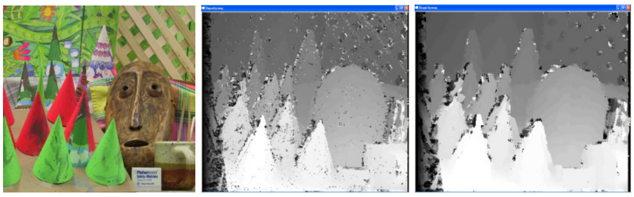
We also measured the time needed to process stereo images by our method. Table 1 contains the measured processing times of the different components for each stereo pair. The timing tests were performed on a PC with a Pentium IV, 3.0 GHZ and visual studio 2005. We note that the computation time mainly depends on the image size. As it can be seen, the most expensive computation step is the initial disparity map calculated by the BP network.

a) Left and right image.

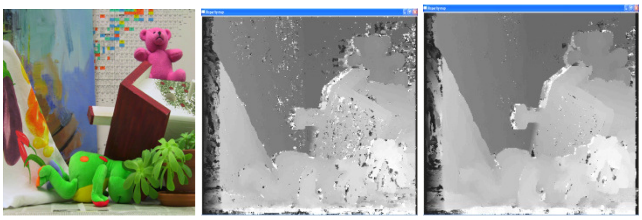


b) The segmented images.

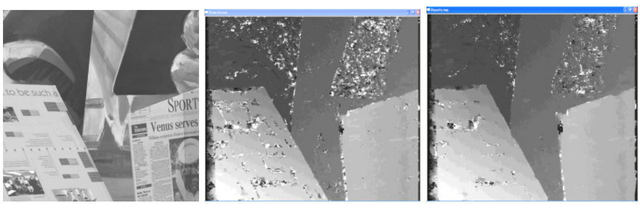
Figure 11. Result of the segmentation method on the image pair.



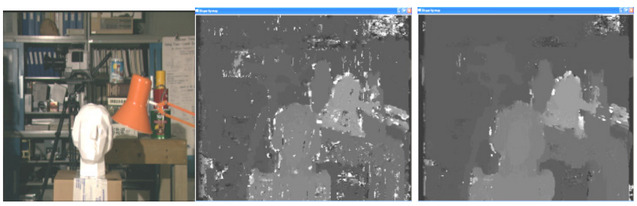
a) Cones



b) Teddy



c) Venus



d) Tsukuba

Figure 12. Results of final disparity map: from left to right, real images, initial disparity maps, and final disparity maps.

Table 1. Processing times of each image for different steps of our method.

Task	Images and Resolution			
	Cones (450x375)	**Teddy (450x375)**	**Venus (434x384)**	**Tsukuba (384x288)**
Primitives Extraction	0.88	0.77	0.67	0.65
Matching and Training	2.81	2.33	2.92	1.89
Initial Disparity (BP)	170	163	162	82
Segmentation	0.16	0.13	0.13	0.11
Refinement	120	114	102	54

4. Conclusions

In this paper, we have presented a new approach for computing dense disparity map based on the neural network from a pair of stereo images. The disparity map computing process is divided on to two main steps. The first one deals with computing the initial disparity map by using a neuronal method (BP). The second one presents a very simple and fast method to refine the initial disparity map by using image segmentation so an accurate result can be achieved. In order to accelerate the refinement process. We have also implemented an algorithm to find the corresponding segments between the left and the right image based on similarity. As such, our method is more like a combination of the area-based and features-based method.

Our objective in this study was to investigate the potentialities of neural method in the field of disparity map computing. In the future work, and in order to reduce the computation time, we will implement the algorithms on a field programmable gate array: FPGA, the processing time can be further reduced. In addition, we have to develop a more powerful segmentation algorithm. The performance of the segmentation decides the efficiency and the quality of the final disparity map.

References

[1] Alvarez L., Deriche R., Sanchez J., and Weickert J., "Dense Disparity Map Estimation Respecting Image Discontinuities: a PDE and Scalespace Based Approach," *Journal of Visual Communication Image Represent*, vol. 13, no. 1-2, pp. 3-21, 2002 .

[2] Baha N. and Larabi S., "Obstacle Detection from Uncalibrated Cameras," *in Proceedings of Panhellenic Conference on Informatics*, Samos, pp. 152-156, 2008.

[3] Bartoli A. and Sturm P., "Non Linear Estimation of the Fundamental Matrix with Minimal Parameters," *IEEE Transaction on Pattern Analysis and Machine Intelligence,* vol. 26, no. 4, pp. 426-432, 2004.

[4] Binaghi E., Gallo I., Fornasier C., and Raspanti M., "Growing Aggregation Algorithm for Dense Two-Frame Stereo Correspondence," *in Proceedings of 1st International Conference on Computer Vision Theory and Application,* Germany, pp. 326-332, 2006.

[5] Bobik A. and Intille S., "Large Occlusion Stereo," *International Journal on Computer Vision*, vol. 33, no. 3, pp. 181-200, 1999.

[6] Cochran S. and Medioni G., "3-D Surface Description from Binocular Stereo," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 14, no. 10, pp. 981-994, 1992.

[7] Fehn C., Cooke E., Schreer O., and Kauff P., "3D Analysis and Imagebased Rendering for Immersive TV Applications," *Signal Processing Image Communication*, vol. 17, no. 9, pp. 705-715, 2002.

[8] Feiner S., MacIntyre B., and Seligmann D., "Knowledge-Based Augmented Reality," *Communication ACM*, vol. 36, no. 7, pp. 53-62, 1993.

[9] Gonzalez R. and Woods R., *Digital Image Processing*, Addison-Wesley Reading, USA, 1992.

[10] Goulermas J. and Liatsis P., "Hybrid Symbiotic Genetic Optimisation for Robust Edge-Based Stereo Correspondence," *Pattern Recognition*, vol. 34, no. 12, pp. 2477-2496, 2001.

[11] Grimson W., "Computational Experiments with a Feature Based Stereo Algorithm," *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 7, no. 1, pp. 17-34, 1985.

[12] Harris C. and Stephens M., "A Combined Corner and Edge Detector," *in Proceedings of 4th Alvey Vision Conference Manchester*, UK, pp. 147-151, 1988.

[13] Hartley R., "Theory and Practice of Projective Rectification," *International Journal on Computer Vision*, vol. 35, no. 2, pp. 115-127, 1999.

[14] Haykin S., *Neural Network: A Comprehensive Foundation*, Pentice Hall, USA, 1998.

[15] Hecht R., "Counter Propagation Networks," *IEEE International Conference on Neural Networks*, vol. 26, no. 23, pp. 4979-4983, 1987.

[16] Iddan J. and Yahav G., "3D Imaging in the Studio and Elsewhere," *in Proceedings of SPIE 3D Image Capture and Applications IV*, Israel, pp. 48-55, 1994.

[17] Kanade T., Yoshida A., Oda K., Kano H., and Tanaka M., "A Stereo Machine for Video-Rate Dense Depth Mapping and its New Applications," *in Proceedings of IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, USA, pp. 196-202, 1996.

[18] Kanade T. and Okutomi M., "A Stereo Matching Algorithm with An Adaptive Window: Theory

and Experiment," *IEEE Transaction Pattern Analysis and Machine Intelligence*, vol. 16, no. 9, pp. 920-932, 1994.

[19] Kumar S. and Chatterji B., "Stereo Matching Algorithms Based on Fuzzy Approach," *International Journal of Pattern Recognition and Artificial Intelligence*, vol. 16, no. 7, pp. 883-899, 2002.

[20] Levenberg K., "A Method for Solution of Certain Non-Linear Problems in Least Squares," *Quarterly Journal of applied Mathematics*, vol. 11, no. 2, pp. 164-168, 1944.

[21] Luong Q. and Faugeras O., "The Fundamental Martix: Theory, Algorithms, and Stability Analysis," *International Journal of Computer Vision*, vol. 17, no. 1, pp. 43-75, 1996.

[22] Miled W. and Pesquet J., "Dense Disparity Estimation from Stereo Images," *in Proceedings of 3rd International Symposium on Image/Video Communication,* Tunisie, 2006.

[23] Mostefaoui S., "Emergence in Collective Robotics: A Case Study," *The International Arab Journal of Information Technology*, vol. 1, no. 0, pp. 47-53, 2003.

[24] Nasrabadi N. and Choo C., "Hopfield Network for Stereo Vision Correspondence," *IEEE Transactions Neural Networks*, vol. 3, no. 1, pp. 5-13, 1992.

[25] Nevatia R. and Babu K., "Linear Feature Extraction and Detection," *Computer Graphics Image Processing*, vol. 13, no. 1, pp. 257-269, 1980.

[26] Reskó B., Berany P., and Hashimoto H., "Camera Control with Disparity Matching Stereo Vision by Artificial Neural Networks," *in Proceedings of WISES*, US, pp. 139-150, 2003.

[27] Scharstein D. and Szeliski R., "A Taxonomy and Evaluation of Dense Two-Frame Stereo Correspondence Algorithms," *International Journal on Computer Vision*, vol. 47, no. 1-3, pp. 7-42, 2002.

[28] Simond N., "Obstacle Detection from IPM and Super-Homography," *in Proceedings of IEEE IROS International Conference on Robot and System*, CA, pp. 4283-4288, 2007.

[29] Zhang Z. and Loop C., "Computing Rectifying Homographies for Stereo Vision," *in Proceedings of IEEE Conference on Computer Vision and Pattern Recognition*, USA, pp. 125-131, 1999.

[30] Zhong L., *Methodes Robustes en Vision: Application Aux Appariements Visuels*, Thèse de Doctorat de L'INP de Grenoble, 1997.

[31] Tardif P. and Zaccarin A., *Segmentation D'images De Textures Par Des Modeles Multiresolutions*, Univerité Laval, 2000.

[32] Middlebury, available at: http:// vision.middlebury.edu/stereo, last visited 2007.

Nadia Baha received the Magister in computer science at CDTA in 1991. She is currently a PhD student and a researcher at the Computer Science Institute of University of Sciences and Technologies (USTHB), Algeria. She is an author of numerous publications for conferences, proceedings. Her research interests include computer vision and mobile robot navigation.

Slimane Larabi received the PhD in computer science from the National Institute Polytechnic of Toulouse, France, in 1991. He is currently Professor at the computer Science Institute of USTHB University, where he conducts research on Computer Vision. His interest topics are Image description, Human action recognition, Head pose estimation, knowledge modelling and representation for computer vision.